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# Application of Vector Error Correction Model on Inflation and Gross Domestic Product

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***Abstract:*** *Inflation and Gross Domestic Product (GDP) are key macroeconomic indicators that reflect the economic condition of a country. This study aims to analyze the factors that influence inflation and GDP in Indonesia using the Vector Error Correction Model (VECM) approach. This method is chosen to accommodate time series data that are not stationary but have a cointegrating relationship. This study uses quarterly secondary data from 2015 to 2023, including various variables such as inflation, export value, import value, interest rates, and GDP. The results show that inflation and GDP have a significant influence in both the short and long run. In addition, imports and interest rates have a significant impact on GDP, while exports show no significant effect. Granger Causality testing reveals a unidirectional relationship between imports, exports, and interest rates, where interest rates can predict exports and imports. Impulse Response Function (IRF) analysis shows the dynamic interaction between inflation and GDP, where both show a complex response to disturbances in a given period. Variance Decomposition shows that the effect of GDP on inflation increases gradually, reflecting the increasingly strong relationship between these two variables. This study highlights the importance of managing stable inflation and inclusive economic growth to support sustainable development. The results of this study can serve as a basis in formulating economic policies that support macroeconomic stability in Indonesia.*

**Keywords — Inflation; Gross Domestic Product; Vector Error Correction Model (VECM); Time Series; Regression**

## 1. INTRODUCTION

The economy plays an important role in creating community welfare. As the main foundation of development, economic stability has a significant impact on purchasing power, job creation, and improving quality of life. In this context, a healthy economy is one of the prerequisites for achieving the goals of sustainable development and equitable welfare throughout society [1]. As the largest developing country in Southeast Asia, Indonesia continues to record economic growth despite facing challenges such as social inequality, price fluctuations, and global economic pressures. However, Indonesia remains one of the largest economies in ASEAN, competing with Singapore and Thailand [2]. In an effort to improve its competitiveness in the region, Indonesia needs to pay special attention to the management of inflation and Gross Domestic Product (GDP) growth as two key indicators that reflect a country's macroeconomic conditions [3].

Inflation is one of the important indicators in analyzing a country's economy, especially with regard to its broad impact on aggregate macroeconomic variables, namely economic growth, external balance, competitiveness, interest rates and even income distribution [4]. A country's economy can be said to be healthy if its economic growth is stable and shows a positive direction. To see the stability of a country's economy is reflected in the stable inflation rate. High and unstable inflation indicates that there is a tendency for the price level of goods and services to rise in general and continuously so as to make people's purchasing power weaker and have an impact on reducing national income.

Economic growth is the process of increasing output per capita in the long term, which reflects welfare through increased consumption, purchasing power, and production of goods and services. This growth is measured by the increase in national income, which is seen in the value of Gross Domestic Product (GDP) which fluctuates from year to year [5]. According to data from the International Monetary Fund (IMF) in 2023, Indonesia is included in the 20 countries with the largest economies in the world. Meanwhile, the Central Bureau of Statistics (BPS) reported that in the fourth quarter of 2023, Indonesia's GDP grew by 5.04%. However, this figure is still below the economic growth target set in the 2020-2024 Medium-Term Development Plan, which is 5.6% to 6.2%. This difference between target and realization reflects the challenges Indonesia faces to achieve higher economic growth. The success of a country in overcoming its economic problems can be assessed through macro and micro economic performance [6].

In the context of sustainable development, managing manageable inflation and inclusive and sustainable economic growth are crucial. Stable inflation and sustainably growing GDP directly contribute to the achievement of the Sustainable Development Goals (SDGs), especially in the goal of creating decent work and economic growth in point 8, and reducing social inequality in point 10. Indonesia has also implemented several policies in maintaining these macroeconomic indicators, for example, monetary policies that play a role in maintaining Indonesia's economic stability and fiscal policies that can optimize state revenues by

maintaining the investment and business climate, as well as environmental sustainability. Therefore, understanding the factors that influence macroeconomics in Indonesia is a strategic step to formulate economic policies that support sustainable development.

To analyze the factors that affect the macroeconomy in Indonesia, a method is needed that is able to identify the relationship between variables. One method that is often used is regression analysis, which is effective for measuring the effect of independent variables on dependent variables [7]. In addition, the Vector Autoregression (VAR) method, introduced by Christopher Sims in 1980, is a development of Granger's (1969) theory. Granger stated that if there is a causal relationship between two variables, such as X affects Y, then historical data of X can be used to predict Y. The VAR approach in reduced form avoids structural modeling by making each endogenous variable a function of the lag values of other endogenous variables. VAR model estimation uses the Ordinary Least Square (OLS) method and allows separate modeling for each endogenous variable. If the VAR model shows a cointegration relationship, further analysis is required using the Vector Error Correction Model (VECM). Cointegration is a linear combination between nonstationary variables, where all variables must be integrated at the same order or level [8]. In general, cointegration is used to identify the long-run equilibrium relationship between variables. VECM is an extension of the VAR model designed for nonstationary data with cointegrating relationships. Therefore, VECM is a suitable alternative method to handle non-stationary data with cointegration, so that the VAR model becomes restricted.

A study by Firdaus et al. [9] also found that interest rates have a significant influence on inflation in Indonesia through multiple linear regression. A study by Jumhur et al. [10] using the Ordinary Least Square (OLS) method shows that Indonesia's inflation is influenced by exports and imports. On the other hand, Puspita & Nurlatipah [11] concluded that exports have a positive impact on the exchange rate, but imports have a different impact depending on the economic situation. A study by Affandi et al. [12] investigated the impact of Indonesia's imports and exports on GDP using the generalized Least square (GLS) method and found that imports and exports have a significant impact on GDP. This finding is supported by the research of Ria et al. using panel data regression. Hakim [13] used multiple regression analysis to find that interest rates have a positive impact on economic growth in Indonesia, and low interest rates encourage increased investment and economic growth [14].

Based on research from previous researchers, this study will analyze the factors that influence macroeconomics in Indonesia using the VECM approach. The novelty of this research is that it uses two exogenous variables simultaneously which has never been done by previous researchers, namely Inflation and Gross Domestic Product (GDP). In addition, the use of the VECM method is based on the structure of time series data that is not stationary, there is cointegration, and multivariate that meets the analysis using the VECM approach.

## 2. LITERATURE REVIEW

### 2.1 Unit Root Test

A variable is said to be stationary if it shows no trend and does not spread randomly without returning to its average value, or in other words, the variable has a data distribution pattern around its average value. To test stationarity in time series data, one method that is often used is the unit root test. Time series data is declared stationary if it does not contain unit roots [15]. The testing process with the unit root test starts with a model that follows a stochastic pattern as stated in the following equation.

$$y_t = \rho y_{t-1} + \boldsymbol{x_t'}\mu + \boldsymbol{\epsilon_t} \quad (1)$$

where $\boldsymbol{x_t}$ is an optional regressor variable that contains a constant, $\boldsymbol{\epsilon_t}$ is an error term that is white noise. The variable $\boldsymbol{y_t}$ is said to have a unit root if the autoregressive coefficient is equal to one ($\rho = 1$). Meanwhile, a series that has a unit root is called a random walk that follows the stochastic process of a nonstationary model.

Based on equation (1), a model can be written to test the parameter $\delta$ if there is a first-order difference operator,

$$\Delta y_t = \delta y_{t-1} + x_t'\gamma + \epsilon_t \quad (2)$$

with, $\delta = \rho - 1$.

The unit root test is further developed using the Augmented Dickey-Fuller (ADF) method. The model equation for the ADF test is as follows.

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + v_t \quad (3)$$

with, $\Delta y_t$ is the difference of endogenous variables at time $t$ and $t-1$ of $q \times 1$ dimension, $\Delta y_{t-i}$ is the difference of endogenous variables at time $t-1$ and $t-i-1$ of $q \times 1$ dimension, $\delta$ is the first lag parameter, and$v_t$ is the error vector of $q \times 1$ dimension.

### 2.2 Vector Autoregression (VAR)

The Vector Autoregression (VAR) model is a system of equations in which each variable is expressed as a linear function of a constant, the lag value of the variable itself, and the lag value of other variables in the system. The VAR method has several assumptions that must be met, namely all independent variables must be stationary (have constant mean, variance, and covariance) and all covariates must be white noise, meaning they have zero mean, constant variance, and are not correlated with each other [16].

The q-dimensional VAR(p) stationary process can be seen as follows.

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \boldsymbol{B_1 y_{t-1}} + \boldsymbol{B_2 y_{t-2}} + \cdots + \boldsymbol{B_p y_{t-p}} + \boldsymbol{A x_t} + \boldsymbol{\epsilon_t} \quad (4)$$

The vector of endogenous variables, denoted as $\boldsymbol{y}_t = (y_{1t}, y_{2t}, \dots, y_{qt})'$, is a the $q \times 1$ dimensional vector representing the time series of interest. In contrast, the vector of exogenous variables, denoted as $\boldsymbol{x}_t = (x_{1t}, x_{2t}, \dots, x_{dt})'$, is an $d \times 1$ dimensional vector representing the external factors that may influence the endogenous variables, $\boldsymbol{\mu}$ is a vector $q \times 1$ of parameters, the matrices $\boldsymbol{B}_1, \boldsymbol{B}_2, \dots, \boldsymbol{B}_p$ are $q \times q$ matrices of estimated lag coefficients, which capture the relationships between the endogenous variables across different time lags. Additionally, $\boldsymbol{A}$ is $q \times d$ matrix of estimated coefficients for the exogenous variables, representing the impact of these external factors on the endogenous variables. The error term $\boldsymbol{\epsilon}_t = (\epsilon_{1t}, \epsilon_{2t}, \dots, \epsilon_{qt})'$ is $q \times 1$ white noise error vector, assumed to have a mean of zero, $E(\boldsymbol{\epsilon}_t) = \mathbf{0}$, and a covariance matrix $cov(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t') = \Sigma_\epsilon$, with no autocorrelation, meaning $cov(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_s') = \mathbf{0}$ for $t \neq s$ [17].

The error assumption states that the error vector is simultaneously correlated with a full rank $\Sigma_\epsilon$ matrix, but there is no correlation across time. In addition, it is assumed that $\boldsymbol{x}_t$ has no correlation with the error vector. For example, the vector has dimension $(pq + d + 1) \times 1$.

$$\boldsymbol{Z}_t = \left(1, \boldsymbol{y}_{t-1}', \boldsymbol{y}_{t-2}', \dots, \boldsymbol{y}_{t-p}', \boldsymbol{x}_t'\right)' \tag{5}$$

Expressing all regressors in period t in the VAR($p$) model, then for each observation $t = 1, 2, \dots, T$, the VAR(p) model in equation (4) can be written in the form of a more concise system as in equation (6).

$$\mathbf{Y} = \mathbf{CZ} + \mathbf{E} \tag{6}$$

with, $\mathbf{Y} = (\boldsymbol{y}_1, \boldsymbol{y}_2, \dots, \boldsymbol{y}_T)$ and $\mathbf{E} = (\boldsymbol{\epsilon}_1, \boldsymbol{\epsilon}_2, \dots, \boldsymbol{\epsilon}_T)$ are $q \times T$ matrices representing the endogenous variables and errors, respectively, while $\mathbf{C} = (\boldsymbol{\mu}, \boldsymbol{B}_1, \boldsymbol{B}_2, \dots, \boldsymbol{B}_p, \boldsymbol{A})$ and $\mathbf{Z} = (\boldsymbol{Z}_1, \boldsymbol{Z}_2, \dots, \boldsymbol{Z}_T)$ are $q \times (pq + d + 1)$ matrices for the coefficient system and $(pq + d + 1) \times T$ matrices for the regressor data, respectively. Model (6) can be written in vector form as equation (7).

$$\tilde{\boldsymbol{y}} = \left(\mathbf{Z}' \otimes \mathbf{I}_q\right)\boldsymbol{\gamma} + \tilde{\boldsymbol{\epsilon}} \tag{7}$$

with, $\tilde{\boldsymbol{y}} = \text{vec}(\mathbf{Y})$, $\boldsymbol{\gamma} = \text{vec}(\mathbf{C})$, and $\tilde{\boldsymbol{\epsilon}} = \text{vec}(\mathbf{E})$, the parameter estimation of the VAR(p) model in equation (7) is performed using the Ordinary Least Squares (OLS) method.

$$\hat{\boldsymbol{\gamma}} = \left[(\mathbf{ZZ}')^{-1}\mathbf{Z} \otimes \mathbf{I}_q\right]\tilde{\boldsymbol{y}} \tag{8}$$

The properties of the OLS estimator $\hat{\boldsymbol{\gamma}}$ are as follows:.

$$E(\hat{\boldsymbol{\gamma}}) = \boldsymbol{\gamma} \text{ and } cov(\hat{\boldsymbol{\gamma}}) = (\mathbf{ZZ}')^{-1} \otimes \Sigma_\epsilon \tag{9}$$

To obtain the covariance matrix estimator, an estimate of $\Sigma_\epsilon$ is required, which is generally calculated using the corrected residual moment estimate as follows:

$$\hat{\Sigma}_\epsilon = \frac{\hat{\mathbf{E}}\,\hat{\mathbf{E}}'}{n - (pq + d + 1)} \tag{10}$$

### 2.3 Vector Error Correction Model (VECM)

The Vector Error Correction Model (VECM) is a specialized form of VAR designed to handle non-stationary data that has cointegration. In VAR, endogenous variables affect each other, where each variable is explained by its own past values and by other endogenous variables. VARs generally do not involve exogenous variables and are used for economic forecasting and cause-and-effect relationship analysis. However, when the data is non-stationary, VAR estimation may result in bias. Therefore, VECM is applied by including error correction using the first derivatives of the variables integrated at the first level [18].

In general, the VECM model can be expressed in the following equation.

$$\Delta \boldsymbol{y}_t = \boldsymbol{\Pi} \boldsymbol{y}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t \tag{11}$$

with, $\Delta$ is the differencing operator, $\boldsymbol{\Pi} = \sum_{i=1}^{p} B_i - I$, $\Gamma_i = -\sum_{j=i+1}^{p} B_j$ $Y_t$ is the vector of endogenous variables, $\boldsymbol{y}_{t-1}$ is the vector of endogenous variables with lag 1 of size $n \times 1$, $p - 1$ is the VECM lag $\Gamma_i$ is the coefficient matrix of the $i$-th endogenous variable of size $n \times n$, $\boldsymbol{\varepsilon}_t$ is the residual vector of size $n \times 1$ [19].

### 2.4 Optimal Lag Determination

According to Rosadi [20], the selection of the optimal lag order $p$ can be done using the Akaike information criterion, better known as AIC (Akaike Information Criterion). AIC is formulated as follows:

$$AIC(p) = \log det\left(\hat{\Sigma}_u(\hat{\epsilon})\right) + \frac{2pq^2}{T} \tag{12}$$

with, $\left(\hat{\Sigma}_u(\hat{\epsilon})\right) = T^{-1}\sum_{t=1}^{T} \hat{u}_t \hat{u}_t'$, $T$ represents the sample size, while $k$ indicates the number of endogenous variables. The lag value of $p$ is chosen as $p*$, which is the value of $p$ that minimizes the information criterion in the observed interval 1, ... , p_max [20].

### 2.5 Cointegration Test

The VAR cointegration test uses the methodology developed by Johansen, which is performed using group objects or estimated VAR objects [21, 22].

Consider a VAR of order $p$:

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \boldsymbol{B}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{B}_p \boldsymbol{y}_{t-p} + \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{\epsilon}_t \tag{13}$$

where, $y_t$ is a k-vector of non-stationary I variables, $x_t$ is a d-vector of deterministic variables, and $\epsilon_t$ is a vector of innovations. We can rewrite this VAR as,

$$\Delta \boldsymbol{y_t} = \boldsymbol{\mu} + \prod \boldsymbol{y_{t-1}} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \boldsymbol{y_{t-i}} + \boldsymbol{C}\boldsymbol{x_t} + \boldsymbol{\epsilon_t} \tag{14}$$

where,

$$\boldsymbol{\Pi} = \sum_{i=1}^{p} \boldsymbol{B_i} - \boldsymbol{I}, \qquad \boldsymbol{\Gamma_i} = -\sum_{j=i+1}^{p} \boldsymbol{B_j} \tag{15}$$

The Granger representation theorem states that if the coefficient matrix $\prod$ has a reduced rank $d < T$, then there are matrices $\alpha$ and $\beta$ of size $q \times d$, each with rank $d$,so that $\prod = \boldsymbol{\alpha\beta'}$ and $\boldsymbol{\beta' y_t}$ are stationary. The value of $r$ describes the number of cointegrating relationships (cointegration rank), where each column of $\beta$ is a cointegrating vector. As explained below, the elements of $\alpha$ are referred to as adjustment parameters in the Vector Error Correction (VEC) model. The Johansen approach involves estimating the unconstrained $\prod$ matrix in a VAR model and testing whether the reduced rank restriction on $\prod$ can be rejected [23].

### 2.6 Stability Test

The stable condition are met if all roots are inside the unit circle, which means the absolute value of the unit root is less than one [20]. According to [14], the model in equation (4) without the regressor variable $\boldsymbol{x}_t$ is expressed as follows.

$$\boldsymbol{y}_t = \boldsymbol{\mu} + \boldsymbol{B}_1\boldsymbol{y}_{t-1} + \boldsymbol{B}_2\boldsymbol{y}_{t-2} + \cdots + \boldsymbol{B}_p\boldsymbol{y}_{t-p} + \boldsymbol{\epsilon}_t \quad (16)$$

Model (16) is considered stable if all roots have a modulus less than 1, so that the composition is in the optimal condition and the model in equation (16) remains stable. This model can be represented as a unitless VAR(1) model, as described in equation (17).

$$\boldsymbol{Y}_t = \boldsymbol{v} + \mathbf{B}\boldsymbol{Y}_{t-1} + \boldsymbol{U}_t \quad (17)$$

with,

$$\boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{y}_t \\ \vdots \\ \boldsymbol{y}_{t-p+1} \end{bmatrix}, \boldsymbol{v} = \begin{bmatrix} \boldsymbol{\mu} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} \boldsymbol{B}_1 & \boldsymbol{B}_2 & \cdots & \boldsymbol{B}_{p-1} & \boldsymbol{B}_p \\ \boldsymbol{I}_q & 0 & \cdots & 0 & 0 \\ 0 & \boldsymbol{I}_q & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{I}_q & 0 \end{bmatrix}, \boldsymbol{U}_t = \begin{bmatrix} \boldsymbol{\epsilon_t} \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Variable $\boldsymbol{Y}_t$ in equation (17) stable can be shown if

$$det(\boldsymbol{I}_{pq} - \boldsymbol{B}z) \neq 0 \; for \; |z| \leq 1 \quad (18)$$

where, $\boldsymbol{I}_{pq}$ is the identity matrix of $(pq \times pq)$, $\boldsymbol{B}_1, \ldots, \boldsymbol{B}_p$ is the coefficient matrix of $(pq \times pq)$ [17].

### 2.7 Granger Causality Test

The Granger Causality Test is used to determine whether an endogenous variable can be considered an exogenous variable. This test aims to identify the dependency relationship between variables. For example, if there are two variables, $X$ and $Y$, then some possible relationships that can occur are $X$ affects $Y$, $Y$ affects $X$, both affect each other, or there is no relationship at all. The variable $X$ is considered to affect $Y$ if the current value of $Y$ can be explained by the value of $Y$ in the previous period as well as the value of $X$ in the previous period [24].

The equation used to conduct the granger causality test can be written as follows [15].

$$X_t = \sum_{i=1}^{m} a_i X_{t-i} + \sum_{j=1}^{n} b_j Y_{t-j} + \mu_t \quad (19)$$

$$Y_t = \sum_{i=1}^{r} c_i X_{t-i} + \sum_{j=1}^{s} d_j Y_{t-j} + v_t \quad (20)$$

To detect the existence of a causal relationship, the F test is used. The formula for calculating the F value is as follows.

$$F = \frac{\frac{(RSS_R - RSS_{UR})}{p}}{\frac{RSS_{UR}}{(n-b)}} \quad (21)$$

In this context, $RSS_R$ represents the residual sum of squares of the restricted (conditional) regression, while $RSS_{UR}$ refers to the residual sum of squares of the unrestricted (unconditional) regression. The parameter $p$ indicates the lag length, $n$ represents the number of observations, and $b$ refers to the number of parameters estimated in the model.

### 2.8 Impulse Response Function (IRF)

The Impulse Response Function (IRF) can be obtained from two types of VAR models, namely VAR that uses variables in levels and VECM that uses variables with I(1) degree of integration that have a cointegration relationship. To obtain IRF from level VAR and VECM, the model needs to be represented in the form of shocks, known as vector moving average (VMA) representation [25]. IRF is used to test VAR models by mapping the response of endogenous variables to shocks from exogenous variables or the variables themselves. The purpose of IRF is to measure the duration and magnitude of the impact of shocks on other variables. These shocks are measured in standard deviations and can be positive, negative or neutral. The IRF is calculated through iterations in the VAR model, which can be adjusted according to the VAR structure used. IRF analysis illustrates how the variables in the system interact and react to changes.

Using the VAR model equation, it is assumed that the general form is stable if

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \mathbf{B}_1^i \boldsymbol{\varepsilon_{t-i}} \quad (22)$$

Then, equation (22) can be simplified into equation (23) as follows

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \textstyle\sum_{i=0}^{\infty} \boldsymbol{\Phi}_i \boldsymbol{\varepsilon_{t-i}} \quad (23)$$

with,

$$\boldsymbol{\Phi}_i = \begin{bmatrix} \emptyset_{11}(i) & \emptyset_{12}(i) & \cdots & \emptyset_{1q}(i) \\ \emptyset_{21}(i) & \emptyset_{22}(i) & \cdots & \emptyset_{2q}(i) \\ \vdots & \vdots & \ddots & \vdots \\ \emptyset_{q1}(i) & \emptyset_{q2}(i) & \cdots & \emptyset_{qq}(i) \end{bmatrix} \quad (24)$$

The coefficients $\emptyset_{jk}(i); j = 1,2,\dots,q$; and $k = 1,2,\dots,q$ are referred to as IRFs which are generally depicted in a graph to define the endogenous variables in response to shocks [18].

### 2.9 Variance Decomposition

Variance decomposition, also known as Variance Decomposition, is used to predict the percentage contribution of variance in each variable to changes in the system [26]. This method reveals the proportion of influence a shock to one variable has on another, both now and in the future. Variance Decomposition estimates the extent to which a variable contributes to changes in itself and other variables in the next few periods, expressed as a percentage [27]. The formula for Variance Decomposition is as follows [17].

$$W_{jk,h} = \frac{\left(\sum_{i=0}^{h-1} e_j' \Theta_i e_k\right)^2}{MSE_j(\mathrm{h})} \qquad (25)$$

$\Theta_i$' is obtained from $A_i$ and $\Sigma_u$ by the formula $\Theta_i = \boldsymbol{\Phi_i P}$, where $\boldsymbol{P}$ is the lower triangular Choleski decomposition of $\Sigma_u$, such that $\Sigma_u = \boldsymbol{PP'}$. We will assume that $\boldsymbol{\Phi_i}$' and $\Theta_i$' are unknown and are calculated based on the estimated VAR coefficients and error covariance matrix.

Here, $e_k$ refers to the kth column of $I_k$

$$MSE_j(\mathrm{h}) = \sum_{i=0}^{h-1} e_j' \boldsymbol{\Phi_i} \Sigma_u \boldsymbol{\Phi_i'} e_j \qquad (26)$$

Is the $j$-th diagonal element of the MSE matrix $\Sigma_u(h)$ of an $h$-step forecast.

## 3. METHODOLOGY

This study examines the impact of export values, import values, and interest rates on macroeconomic indicators using a quantitative approach. It employs statistical data analysis to test predefined hypotheses. The secondary data, sourced from the Central Bureau of Statistics and the Ministry of Trade (MoT), consists of quarterly time series from 2015 to 2023, encompassing 34 districts/cities in Indonesia. The variables used in this study are outlined in Table 1.

**Table 1.** Research of Variables

| Variable | Variable Description | Unit |
|---|---|---|
| $Y_1$ | Gross Domestic Product (GDP) | Ratio |
| $Y_2$ | Inflation | Ratio |
| $X_1$ | Export | Ratio |
| $X_2$ | Import | Ratio |
| $X_3$ | Interest Rate | Percent |

## 4. RESULTS

### 4.1 Descriptive Statistics

Prior to conducting the research, a descriptive statistical analysis will be performed on the variables, including export, import, interest rate, GDP, and inflation. The analysis results are summarized in Table 2 below.

**Table 2.** Descriptives Statistics

| Variable | N | Mean | Stdev | Minimum | Maximum |
|---|---|---|---|---|---|
| GDP | 36 | 2,654,438 | 261,792 | 2,158,040 | 3,139,085 |
| Inflation | 36 | 0.2517 | 0.1759 | -0.1433 | 0.65 |
| Export | 36 | 16,273 | 4,336 | 11,237 | 26,056 |
| Import | 36 | 14,745 | 3,067 | 10,578 | 21,101 |
| Interest Rate | 36 | 5.155 | 1.273 | 3.50 | 7.58 |

In Table 2, Indonesia's Gross Domestic Product (GDP) averaged 2,654,438 billion rupiah, with a standard deviation of 261,792 billion, indicating moderate variability. The GDP ranged between 2,158,040 billion and 3,139,085 billion rupiah. The inflation rate exhibited relatively low variability, averaging 0.2517% with a standard deviation of 0.1759%, and fluctuating between -0.1433% and 0.65%. Exports and imports recorded average values of 16,273 billion and 14,745 billion rupiah, respectively, with exports showing greater variability (standard deviation of 4,336) compared to imports (standard deviation of 3,067). The interest rate averaged 5.155%, with a standard deviation of 1.273%, ranging from a low of 3.50% to a high of 7.58%, indicating relatively stable monetary conditions.

### 4.2 Unit Root Test

Moreover, a stationarity test will be conducted using the ADF method, as presented in Table 3. The purpose of the ADF test is to evaluate whether the data utilized in the study are stationary. Data are deemed stationary if the resulting p-value is less than the significance threshold of 0.05.

**Table 3.** Unit Root Test with ADF Test

| **Real Data** | | | | | |
|---|---|---|---|---|---|
| **Variable** | GDP | Inflation | Export | Import | Interest Rate |
| **ADF Statistic Value** | 0.131 | -5.787 | -0.518 | -0.908 | -2.661 |
| **P-Value** | 0.963 | 0.000 | 0.876 | 0.774 | 0.091 |
| **Data 1$^{st}$ *Differencing*** | | | | | |
| **Variable** | GDP | Inflation | Export | Import | Interest Rate |
| **ADF Statistic Value** | -7.690 | -9.823 | -4.361 | -4.729 | -2.651 |
| **P-Value** | 0.000 | 0.000 | 0.002 | 0.001 | 0.093 |

| Data 2nd Differencing | | | | | |
|---|---|---|---|---|---|
| **Variable** | GDP | Inflation | Export | Import | Interest Rate |
| **ADF Statistic Value** | -9.637 | -6.363 | -6.305 | -6.335 | -5.329 |
| **P-Value** | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 |

The ADF test results indicate that for most variables, stationarity is achieved only after the second differencing, as evidenced by p-value less than the significance level of 0.05. Specifically, the Gross Domestic Product (GDP), exports, imports, and the interest rate become stationary at the second differencing, with all p-value below 0.05. This suggests that these variables require two levels of differencing to meet the stationarity assumption necessary for time series analysis.

### 4.3 Optimal Lag Test

To establish the model, it is necessary to conduct testing to identify the optimal lag. The selection of the optimal lag is based on the AIC value, with the lag corresponding to the lowest AIC value being chosen. The results of the optimal lag test are shown in Table 4 below.

**Table 4.** Optimal Lag Test

| Lag | LogL | LR | FPE | AIC | SC |
|---|---|---|---|---|---|
| 0 | -442.48 | NA | 2.19e+09 | 27.18 | 27.45 |
| 1 | -394.66 | 81.16 | 1.54e+08 | 24.52 | 24.98* |
| 2 | -393.86 | 1.25 | 1.89e+08 | 24.72 | 25.35 |
| 3 | -381.38 | 18.16* | 1.15e+08* | 24.20* | 25.02 |

Based on the results presented in the Table 4, the minimum AIC value is observed at lag 3, with an AIC of 24.20. This indicates that lag 3 is the optimal lag for the model, as it corresponds to the lowest AIC value among the tested lags.

### 4.4 Stability Test

A stability test is performed to confirm the robustness of the estimated model, with the findings presented in Table 5. This test evaluates whether the model adheres to the stability criteria, which is essential for maintaining the precision and dependability of its long-term predictions.

**Table 5.** Stability Test

| Root | Modulus |
|---|---|
| 0.952997 | 0.952997 |
| -0.143886 - 0.857960i | 0.869942 |
| -0.143886 + 0.857960i | 0.869942 |
| -0.622451 | 0.622451 |
| 0.340927 - 0.483754i | 0.591819 |
| 0.340927 + 0.483754i | 0.591819 |

The modulus values of all roots are less than 1, which indicates that the model is stable. Since all the modulus values fall below this threshold, the model meets the stability criteria, ensuring the accuracy and reliability of its long-term predictions.

### 4.5 Cointegration Test

The Johansen Cointegration Test, utilizing the trace statistic, is performed to assess whether cointegration exists among the variables. Cointegration among variables is inferred when the trace statistic surpasses the critical value at the $\alpha$=0.05 significance level.

**Table 6.** Cointegration Test

| Hypothesized No. of CE(s) | Eigen value | Trace Statistic | 0.05 Critical Value | Prob.** |
|---|---|---|---|---|
| None* | 0.469278 | 27.62049 | 15.49471 | 0.0005 |
| At most 1* | 0.205168 | 7.347975 | 3.841465 | 0.0067 |

The Johansen Cointegration Test on Table 6 shows cointegration among the variables, as the trace statistic for both "None" and "At most 1" hypotheses exceeds the critical values, with p-value of 0.0005 and 0.0067. The results indicate that the variables are cointegrated, suggesting the next step is to proceed with the VECM.

### 4.6 VECM Model

The VECM analysis results are shown in Table 7, highlighting the estimated coefficients and their statistical significance. These findings provide valuable insights into the long-term and short-term interactions between the variables, helping to understand their relationships and adjustments toward equilibrium.

**Table 7.** VECM Model

| **Cointegrating Eq:** | **CointEq1** | |
|---|---|---|
| GDP(-1) | 1 | |
| INFLATION(-1) | 1,088,603<br>(401,291)<br>[ 2.71275] | |
| **C** | -2,950,396 | |
| **Error Correction:** | **D(GDP)** | **D(INFLATION)** |
| CointEq1 | -0.163850<br>(0.06098)<br>[-2.68682] | -6.21E-07<br>(2.4E-07)<br>[-2.59609] |
| D(GDP(-1)) | -0.491242<br>(0.18204)<br>[-2.69857] | 2.28E-07<br>(7.1E-07)<br>[ 0.31871] |
| D(GDP(-2)) | -0.741095<br>(0.13850)<br>[-5.35076] | 3.59E-07<br>(5.4E-07)<br>[ 0.66059] |
| D(GDP(-3)) | -0.444154 | 6.20E-07 |

| | | |
|---|---|---|
| | (0.16524) | (6.5E-07) |
| | [-2.68801] | [ 0.95703] |
| D(INFLATION(-1)) | 149280.9 | -0.276853 |
| | (61363.2) | (0.24062) |
| | [ 2.43274] | [-1.15058] |
| D(INFLATION(-2)) | 128809.8 | -0.166415 |
| | (52279.0) | (0.20500) |
| | [ 2.46389] | [-0.81178] |
| D(INFLATION(-3)) | 65157.21 | -0.228718 |
| | (39023.0) | (0.15302) |
| | [ 1.66971] | [-1.49470] |
| C | -386195.9 | -0.596136 |
| | (106282.) | (0.41676) |
| | [-3.63367] | [-1.43040] |
| EXPORT | 0.562583 | 1.73E-05 |
| | -687.820 | (2.7E-05) |
| | [ 0.08179] | [ 0.63992] |
| IMPORT | 2.026.490 | 2.49E-05 |
| | -952.508 | (3.7E-05) |
| | [ 2.12753] | [ 0.66668] |
| INTERESTRATE | 29342.03 | -0.021051 |
| | (10824.7) | (0.04245) |
| | [ 2.71066] | [-0.49594] |
| R-squared | 0.680092 | 0.574653 |
| Adj. R-squared | 0.527755 | 0.372107 |
| Sum sq. resids | 4.09E+10 | 0.628369 |
| S.E. equation | 44113.65 | 0.172981 |
| F-statistic | 4.464388 | 2.837143 |
| Log likelihood | -380.8914 | 17.47979 |
| Akaike AIC | 24.49321 | -0.404987 |
| Schwarz SC | 24.99706 | 0.098860 |
| Mean dependent | 27067.35 | -0.001354 |
| S.D. dependent | 64193.24 | 0.218300 |
| Determinant resid covariance (dof adj.) | | 54,637,659 |
| Determinant resid covariance | | 23,530,476 |
| Log likelihood | | -362.3930 |
| Akaike information criterion | | 24.14956 |
| Schwarz criterion | | 25.24886 |
| Number of coefficients | | 24 |

$$D(GDP) = -0.163849562171 * (GDP(-1) + 1088602.89513 * INFLATION(-1) - 2950395.61904 ) - 0.491241866534 * D(GDP(-1)) - 0.74109471823 * D(GDP(-2)) - 0.444153981675 * D(GDP(-3)) + 149280.884855 * D(INFLATION(-1)) + 128809.755436 * D(INFLATION(-2)) + 65157.2053355 * D(INFLATION(-3)) - 386195.915349 + 0.562582838521 * EXPORT + 20.2649036657 * IMPORT + 29342.0325933 * INTERESTRATE$$

$$D(INFLATION) = -6.20800009759e-07 * ( GDP(-1) + 1088602.89513 * INFLATION(-1) - 2950395.61904 ) + 2.27500767635e-07 * D(GDP(-1)) + 3.58768444805e-07 * D(GDP(-2)) + 6.20084849313e-07 * D(GDP(-3)) - 0.276852665137 * D(INFLATION(-1)) - 0.166414827422 * D(INFLATION(-2)) - 0.228717706955 * D(INFLATION(-3)) - 0.596135833826 + 1.72594345729e-05 * EXPORT + 2.49005442603e-05 * IMPORT - 0.0210509090176 * INTERESTRATE$$

The VECM model regression results are shown in the table above, divided into two sections: the upper part displays the long-term relationship, and the lower part shows the short-term relationship. In the long-term, the results indicate that inflation significantly impacts GDP, with a t-statistic for GDP of 2.71275, which is greater than the critical value of 2.0422.

In the output, GDP and inflation have significant influence on each other both in the short and long term. Imports and interest rates also have significant impact on GDP. However, exports do not show significant influence on GDP. The F-statistic for GDP (4.464388) exceeds the critical value (2.42), suggesting that the independent variables significantly influence GDP. Similarly, the F-statistic for inflation (2.837143) also exceeds 2.42, indicating that the independent variables jointly affect inflation.

The R-squared value for GDP is 0.680092, meaning that exports, imports, and interest rates together explain 68.01% of GDP, while the remaining portion is explained by other

factors. For inflation, the R-squared value is 0.574653, indicating that the independent variables explain 57.47% of inflation, with the remainder explained by other factors.

### 4.7 Granger Causality Test

The Granger Causality test is used to explore the causal relationships between variables. A p-value below the 0.05 significance level indicates short-term causality. The findings of the Granger causality test are summarized in Table 8 below.

**Table 8.** Granger Causality Test

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| IMPORT does not Granger Cause EXPORT | 33 | 1.17085 | 0.3399 |
| EXPORT does not Granger Cause IMPORT | | 3.18491 | 0.0404 |
| INTERESTRATE does not Granger Cause EXPORT | 33 | 3.58855 | 0.0271 |
| EXPORT does not Granger Cause INTERESTRATE | | 0.96925 | 0.4222 |
| INTERESTRATE does not Granger Cause IMPORT | 33 | 2.56585 | 0.0762 |
| IMPORT does not Granger Cause INTERESTRATE | | 1.91440 | 0.1520 |

The results of the Granger causality test indicate that no reciprocal relationship exists between imports and interest rates, as evidenced by the p-value being greater than 0.05. On the other hand, a unidirectional relationship is found between imports and exports, as well as between interest rates and exports, with p-value of 0.0271 and 0.0762, respectively. This implies that interest rates are able to predict exports over the long term, while exports do not have the ability to predict interest rates. Furthermore, interest rates can forecast imports in the long term, whereas imports cannot predict interest rates in the long term.

### 4.8 Impulse Response Function

An Impulse Response Function (IRF) analysis is conducted to examine how variables respond to shocks or disturbances over time. This method offers a detailed understanding of the dynamic interactions between variables. The resulting IRF graph is illustrated in Fig. 1 below.

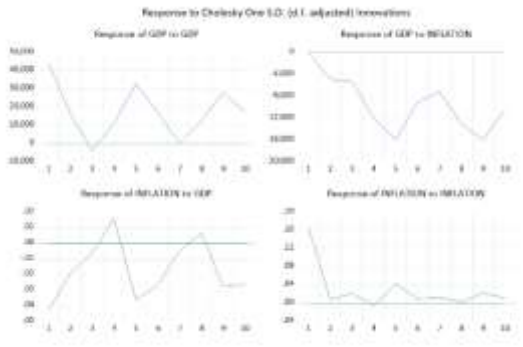

**Fig. 1.** Impulse Response Function (IRF)

The Impulse Response Function (IRF) analysis demonstrates the dynamic interplay between GDP and inflation over a 10-period horizon. GDP exhibits a positive response to its own shocks, reaching a peak around the fourth period before stabilizing, while its response to inflationary shocks is negative, stabilizing below zero over time. Conversely, inflation initially reacts negatively to GDP shocks but transitions to a positive response, peaking between the sixth and seventh periods before stabilizing. Additionally, inflation exhibits a strong initial response to its own shocks, which diminishes sharply and stabilizes near zero in subsequent periods. These findings highlight the intricate interdependencies between GDP and inflation, capturing both short-term fluctuations and long-term stabilization effects.

### 4.9 Variance Decomposition

Table 9 and 10 displays the Variance Decomposition results for the Inflation variable across multiple forecast periods. It highlights the contribution of each response variable to the forecast error variance over time. This analysis offers insights into the changing interactions between inflation and GDP.

**Table 9.** Variance Decompositions of Inflation Variable

| Variance Decomposition of INFLATION: | | | |
|---|---|---|---|
| **Period** | **S,E,** | **GDP** | **INFLATION** |
| 1 | 0.172981 | 6.168062 | 93.83194 |
| 2 | 0.174244 | 7.316486 | 92.68351 |
| 3 | 0.175596 | 7.334944 | 92.66506 |
| 4 | 0.176418 | 8.034449 | 91.96555 |
| 5 | 0.185105 | 11.17775 | 88.82225 |
| 6 | 0.187209 | 12.97820 | 87.02180 |
| 7 | 0.187654 | 12.98403 | 87.01597 |
| 8 | 0.187782 | 13.09057 | 86.90943 |
| 9 | 0.191119 | 14.73692 | 85.26308 |
| 10 | 0.193236 | 16.28136 | 83.71864 |

The Variance Decomposition results for the Inflation variable show that its forecast error variance is initially dominated by Inflation itself, contributing 93.83% in the first period, but this influence declines over time. Meanwhile, GDP's contribution grows significantly, from 6.17% in the first period to 16.28% by the tenth, indicating an increasing

impact on inflation variance. The exchange rate's influence remains minimal, rising slightly from 0.17% to 0.19%. This suggests that inflation is initially self-driven but becomes increasingly affected by GDP over time.

**Table 10.** Variance Decompositions of GDP Variable

| Variance Decomposition of GDP: | | | |
|---|---|---|---|
| **Period** | **S,E,** | **GDP** | **INFLATION** |
| 1 | 44113.65 | 100.0000 | 0.000000 |
| 2 | 47337.67 | 98.94000 | 1.060002 |
| 3 | 47797.49 | 97.71125 | 2.288753 |
| 4 | 50497.81 | 92.24800 | 7.751996 |
| 5 | 62360.88 | 88.40551 | 11.59449 |
| 6 | 65332.76 | 87.47080 | 12.52920 |
| 7 | 65722.40 | 86.43744 | 13.56256 |
| 8 | 68139.64 | 83.73506 | 16.26494 |
| 9 | 75391.49 | 82.16312 | 17.83688 |
| 10 | 77980.20 | 81.52768 | 18.47232 |

The Variance Decomposition results for GDP reveal that its forecast error variance is primarily explained by GDP itself in the early periods, accounting for 100% in the first period and gradually decreasing over time. By the tenth period, GDP contributes 81.53% to its variance, indicating a reduced but still dominant influence. Conversely, Inflation's contribution starts at 0% and increases steadily, reaching 18.47% by the tenth period. This suggests that while GDP initially drives its variance entirely, the influence of Inflation becomes more prominent over extended forecast horizons.

## 5. Conclusions and Suggestions

This study demonstrates that after applying second differencing, the data achieved stationarity, allowing for continued analysis. The optimal lag, determined through the AIC, was found to be lag 3. The Johansen stability and cointegration tests indicate that the model is stable, with a cointegration relationship between the variables, making it suitable for VECM analysis. The results demonstrate that GDP and inflation significantly influence each other in both the short and long term, while imports and interest rates have a notable impact on GDP, though exports do not. The Granger causality test shows a one-way relationship between imports, exports, and interest rates, with interest rates being able to forecast both exports and imports. IRF analysis highlights the dynamic interactions between GDP and inflation over time, and variance decomposition shows that the reciprocal influence between these variables strengthens over time. Future research should consider external factors influencing these variables and take into account potential structural shifts or changes in the economic regime, particularly in the context of global economic fluctuations or policy changes that could affect the relationships between the variables.

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